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# Mitigation of nonlinearities in analog radio over fiber links using machine learning approach

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**Abstract**

Machine learning (ML) techniques are looked upon as an innovative and realistic direction to cope up with nonlinearity issues in fiber optics communication. In this paper, a 64-quadrature amplitude modulation (QAM) based radio over fiber (RoF) system is demonstrated for 10 km of standard single mode fiber length utilizing support vector machine (SVM) method to indicate an effective nonlinearity mitigation in front-hauls. The comparison of SVM is drawn with conventional ML classifiers to optimize symbol decision boundary that will reduce the RoF link impairments. The results are reported in terms of BER, Eye-linearity and Quality factor.


*Keywords:* Radio over fiber; Machine learning; SVM; Eye-linearity

## 1. Introduction

The demand for future wireless networks is increasing day by day. For satisfying this growing demand of data rate, Analog Radio over Fiber (A-RoF) system has been proposed as an empowering technology that improves and extends the wireless coverage and offers high capacity mobility solution to transport information. A-RoF has been employed in different scenarios ranging from inhouse to outdoor applicative scenarios [1–4].

A-RoF systems can serve as building blocks for centralized/cloud radio access network (C-RAN) which connects the base band units (BBU) to remote radio heads (RRHs). The interconnectivity of these BBUs with RRHs through distribution network is referred as the 'fronthaul' [5].

Apart from the advantages coming from A-RoF technology, they also suffer from nonlinearities that arise due to inherent properties of electrical to optical (E–O) and optical to electrical (O–E) conversions [6].

Similarly, the use of long term evolution (LTE) signals suggests the use of orthogonal frequency divisional multiplexing (OFDM) which presents high peak to average power ratio (PAPR) [7]. Since, A-RoF transmission is based on these optical subcarrier modulation techniques, A-RoF links are prone to impairments. Being an economically viable technology, mitigating these nonlinearities is a desired operation.

Similarly, with 5G advancements, the dynamic tracking of increase 5G networks, it would be challenging to dynamically track and compensate the nonlinear channel response, especially given the fact of broadband time varying data traffic from multiple RATs.

Due to these nonlinear impairments in A-RoF systems, the use of Digital Radio over Fiber (D-RoF) as suggested in [5,8] can still be a good option as compared to A-RoF, however, the increase in accuracy, results in increase in resolution bits of analog to digital converters which makes it practically complex and costly operation. The use of Sigma Delta Radio over Fiber system may be used instead of mitigating nonlinearities in A-RoF as suggested in [9,10], however, the increase in quantization noise due to 1-bit of analog to digital converter (ADC) and higher sampling rate is still undesirable. In such situations, A-RoF is still a better choice to be used and employ linearization to such systems. Indeed, due to presence of inexpensive deployment cost and legacy infrastructure that makes it still more preferable than other technologies.

Nonlinearity alleviation results to increase in the optical system capacity. Many techniques have been proposed which mitigate these nonlinearities. Analog predistortion method was

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addressed in [11] where the nonlinearities of the laser source were compensated. Digital Predistortion linearization technique using memory polynomials was discussed in [12], while a trained predistorter based on Volterra series has been applied to non-linear A-RoF link [13,14]. More recently, Digital Predistortion based on memory and generalized memory polynomial was proposed for VCSELs based radio over fiber links [10]. Direct Digital Predistortion technique (DPDT) that linearizes the links by realizing the behavioral model of A-RoF links was also proposed in [6,15]. However, these linearization techniques are complex operations which lead to additional complexities.

The use of machine learning (ML) based classifiers for nonlinear mitigation in A-RoF is comparably a new concept in the optical communications. Recently, in past few years, the use of ML techniques to optical communication system has given an innovative direction. ML can be employed to explicitly describe the challenges in optical fiber communications [16] such as performance optimization, testing, planning and equipment realization. Use of ML-based algorithms for mitigating the nonlinearities of radio over fiber system is a unique concept that should be investigated in detail. In general, these methods learn from the properties of various nonlinear impairments through the applied models which can be utilized for either compensation and quantification of impairments introduced.

Machine learning methodologies such as K nearest neighbor algorithms (KNN), artificial neural networks (ANN) and support vector machines (SVM) are widely used in channel monitoring, modulation format identification, nonlinear compensation, equalization and demodulation [17–19]. SVM based study has been carried out in [20–23] in coherent optical communication system that reduced the fiber induced nonlinearities by 1 dB in comparison to the neural network-based technique. Similar studies have been carried out in [20] where enhanced improvements were reported.

There are two main advantages with ML approaches.

i They can partially mitigate the fiber nonlinearities and noise interactions.
ii The knowledge of optical link is not needed a priori. This tends to make them a good choice for optical networks where dynamic tracking and compensation of link and channel impairments is needed.

In this paper, the mitigation of nonlinear impairments is evaluated by employing SVM based machine learning methods. In the proposed system, a 20 MHz LTE signal with 64 quadrature amplitude modulation (QAM) is injected into distributed feedback (DFB) laser for 100 km single mode fiber transmission. This will cause signal to suffer from nonlinearities caused due to opto-electronic devices in the RoF link as the decision boundary is non-linear. The utilization of SVM method is compared with conventional ML classifier method in order to mitigate the nonlinearities of the RoF link.

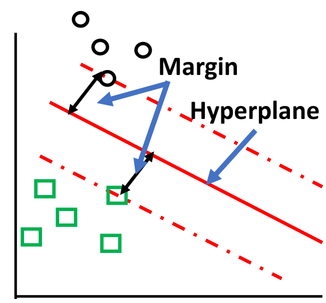


**Fig. 1.** Fundamental SVM classifier.

## 2. SVM decision in RoF system

The separation of one class of data points can be done using SVM classifiers that looks for the best possible hyperplane. The representation of best hyper plane is the one which has largest margin. Similarly, SVM classification relies on finding the best boundary to distinguish two cases. It was shown in [18] that each SVM classifier is responsible for one bit. Since, M-QAM signal requires $\log_2 M$ SVM decisions, therefore 64 QAM will require 6 SVM classifiers.

In order to understand the principle of SVM detection, the separable decision function is represented as:

$$y(x) = sign(\boldsymbol{\omega}.\boldsymbol{x} + b) \tag{1}$$

where $\boldsymbol{\omega}$ and $b$ are the parameters of the hyper-plane. The order of correct classification is defined by functional marginality defined as follows:

$$\widehat{\delta_i} = (\boldsymbol{\omega}.\boldsymbol{x} + b) .y_i \tag{2}$$

where $i = 1, 2, \ldots, N$

The samples are classified correctly when $\widehat{\delta_i} > 0$, therefore the magnitude of $\widehat{\delta_i}$ has no influence in hyper plane itself which means that hyper plane can have many values of $\widehat{\delta_i}$ provided that the proportion of variance between $\boldsymbol{\omega}$ and $b$ remains the same.

From functional marginality, we can defined marginality $\delta$ as explained in [13] as:

$$\delta_i = \frac{|\boldsymbol{\omega}.\boldsymbol{x} + b|}{\|\boldsymbol{\omega}\|}$$

$$\delta = \min_{i=1..N} \delta_i$$

Therefore, the SVM process will become:

$$\max_{\omega,b} \delta \text{ when } \delta_i \geq \delta;\ i = 1, \ldots, N$$

with final optimization target formulated as:

$$\min \frac{1}{2} \|\boldsymbol{\omega}\|^2 \tag{3}$$

In order to solve this functionality, minimal optimization algorithm is used. The fundamental SVM classifier is shown in Fig. 1.

Each signal's bit is labeled as $f_n$, where $n = 1, \ldots, 6$. The designed boundary of each SVM and gray-coded constellation diagram for 64-QAM are shown in Fig. 2.

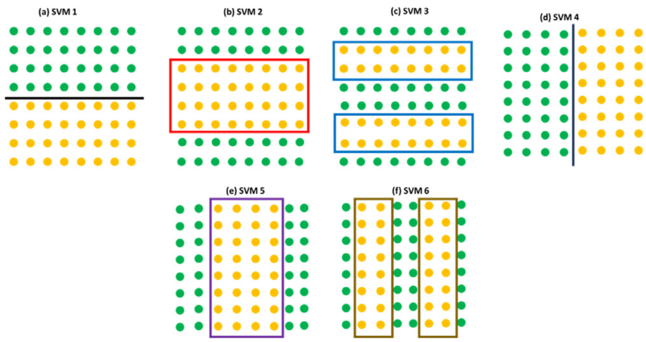


**Fig. 2.** SVM decision for 64 QAM signal. . (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The first and fourth bits have linear classification represented by SVM1 and SVM4, where the test data of the constellation points above the black line and at right side of the blue line marked as “+1” and others are marked as “−1”. SVM2 up to SVM6 are non-linear classifiers, whose test point of the constellation points inside the rectangle closure are referred to “+1” and others as “−1”.

The conventional classifier that we used in this study is a maximum likelihood classifier (MLC) that is generally used as a conventional solution. MLC is based on Bayesian statistics and provides parametric approach in decision making. MLC has been well explained in [24–27]. The mathematical description utilized int his work regarding conventional ML/MLC has been taken from [24].

## 3. Simulation setup

The analytical model demonstrates the model of the RoF systems which is shown in Fig. 3. The model has been realized using a VPI photonics simulator. Input comprises of 64 QAM LTE 20 MHz signal. The SVM decisions are performed in MATLAB. The electro optical (E–O) converter consists of distributed feedback laser (DFB) emitting wavelength at 1550 nm. After 100 km standard single mode fiber (SSMF) transmission, the signal is sent to the photo diode (PD) having center frequency of 3.5 GHz. Details are given in Table 1 of the simulation setup.

The received signal is sent to Baseband DSP block of signal analyzer after which it is passed through post processing process where machine learning decision are carried out followed by the parametric evaluation block.

The steps involved in SVM implementation are as follows:

1. Firstly, the data is transmitted synchronously to each of the SVMs.
2. The parametric optimization is performed for six SVM classifiers.
3. Error bits are counted by comparing the labeled data with original data.

Consider (100 011) as a constellation data received for SVM decision. Primarily, the test data is transferred to SVM1

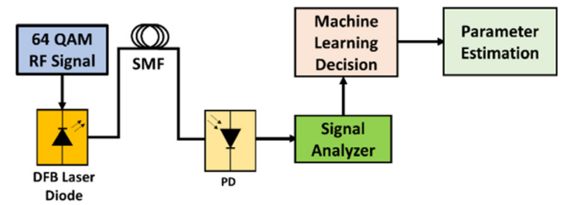


**Fig. 3.** Experimental bench for comparison of conventional ML classifiers and SVM.

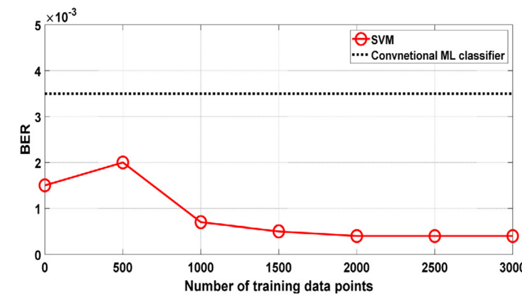


**Fig. 4.** BER versus number of training data points for SVM compared with conventional ML classifier.

**Table 1**
System parameters.

| Parameter | Value |
|---|---|
| **RF signal** | |
| Carrier frequency | 3.5 GHz |
| Constellation | 64 QAM |
| Symbol rate | 16 MSymbols/s |
| **Laser** | |
| Wavelength | 1550 nm |
| Average power | 10 mW |
| Line width | 16 MHz |
| **Fiber** | |
| Fiber dispersion | 16 ps/nm km |
| Fiber distance | 100 km |
| Attenuation | 0.2 dB/km |
| **Photo-detector** | |
| Responsivity | 0.9 A/W |

where the first bit “1” is classified and labeled as “1” by SVM1 decision. Secondly, it is sent to SVM2 and the second bit “0” is labeled as “−1”. Finally, the test data is sent to SVM3, SVM4 and SVM5, where the third, fourth and fifth bits are labeled as “−1”, “−1” and “+1”, respectively.

Finally, SVM6 receives the data and it classifies the sixth bit “1” as “+1”. Once all the test data are labeled, we recalculate the BER of six bits data. As a result, all constellation points of 64-QAM signal can be decided correctly by the six SVMs.

For comparative study, the modulation format has been modified from 64 QAM to 16 QAM and instead of 20 MHz LTE signal, 5 and 10 MHz LTE signal are also considered in results shown in Figs. 8 and 9 We also change fiber length from 100 km to 1000 km in order to see the effect of the proposed methodology.

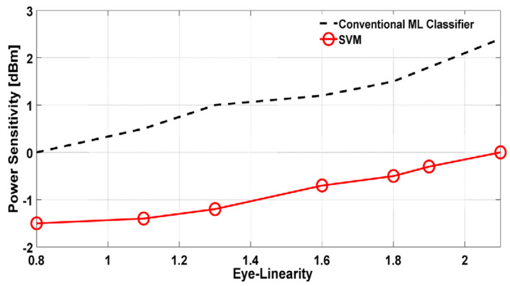


**Fig. 5.** Power sensitivity versus Eye linearity for SVM compared with conventional ML classifier.

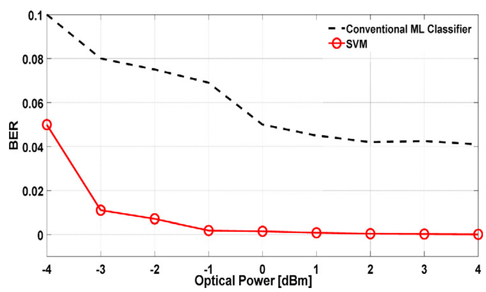


**Fig. 6.** BER versus optical power for SVM compared with conventional ML classifier.

## 4. Simulation results and discussion

The simulation results are discussed in this section. Fig. 4 represents the bit error rate (BER) versus number of training data points. SVM is compared with respect to conventional machine learning classifiers as explained in [14,15,20] for comparison. It is shown for training data smaller than 500 units, SVM performance is efficient because the training samples are only utilized for finding the difference in marginal boundaries. When the number of training data is larger than 1500 or more, SVM saturates the improvement in performance because for SVM decision, the test point is only needed and six SVMs boundary's distance.

Fig. 5 shows the behavior of optical power sensitivity with increase in eye linearity (increase of modulation nonlinearity distortion). It shows that the SVM machine learning performance is less affected by the increase of eye-linearity. Similarly, the smaller slope means an increased sensitivity gain with the increase of eye-linearity.

Similarly, in Fig. 6, BER is reduced significantly when SVM detection is compared with conventional detection. Conventional ML classifier results in reduction of BER with increasing received optical power. However, it can be seen that SVM based detection has BER which saturates in reduction after 0 dBm of optical power.

In Fig. 7, the amplitude is changed from 0.1 to 0.8 volts. It is observed that with the lower amplitude, the nonlinearity is negligible. However, when the adjacent channel leakage ratio is high, the nonlinearity of the link becomes worse. The SVM decision improves the BER performance when compared with conventional ML classifier decision.

Similarly, a Q-factor for 64 QAM modulation with reference to input launch power is compared in Fig. 8 with

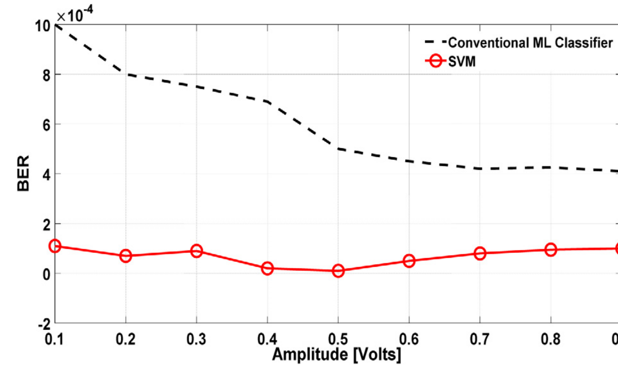


**Fig. 7.** BER versus change in driver amplitude for SVM compared with conventional ML classifier.

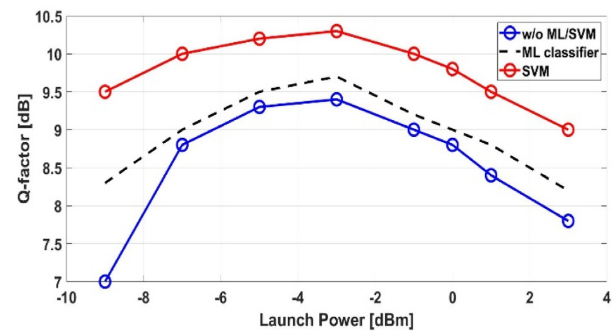


**Fig. 8.** Q-factor versus launch power for SVM compared with conventional ML classifier and without ML/SVM.

traditional ML classifier method and the case when there is no method for improvement with 1000 km fiber length. We show the performance with SVM, with ML classifier and the case where no method is employed. The results signify that Q-factor for SVM method is always above 9.5 dB up till 2 dBm, however, for ML classifier, the results are always better than the case with no ML/SVM method.

Similarly, Q-factor is compared with fiber distance up to 1000 km for −5 dBm of RF input power for SVM, ML classifier and without SVM/ML method. We have chosen 1000 km as a distance as we would like to show that the capability of mitigation is not only for front haul scenarios but could also be applied to back haul as well. The maximum improvement with SVM reduces the fiber induced nonlinearity penalty by about 2.2 dB which is seen at 200 km. These fibers induced nonlinearity penalty improvements in Figs. 8 and 9 are comparable to results shown in [20–28] where 16 QAM modulation is shown up to 1200 km.

Moreover, the eye diagrams with SVM and without any compensation methods are shown at 100 km in Fig. 10. The results verify that SVM is a better eye opener as compared to conventional method.

## 5. Conclusions

The article demonstrated a novel signal decision approach implementation for RoF system where SVM classifier was

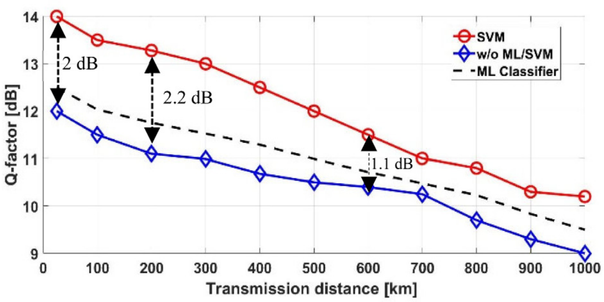


**Fig. 9.** Q-factor versus transmission distance for SVM compared with conventional ML classifier and without ML/SVM.

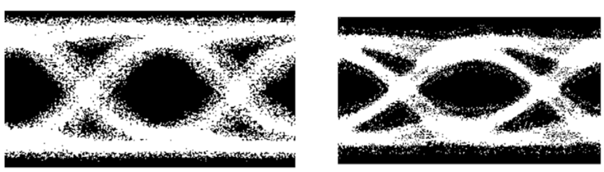


**Fig. 10.** Eye diagrams at 100 km for (a) SVM compared with (b) conventional ML classifier shows suppression in the latter case.

compared with conventional ML classifier in order to see the impact on mitigation of nonlinearity in RoF system. The simulation results show that for 20 MHz LTE signal, 64 QAM modulation having 100 km of fiber length, SVM results in reduction of the bit error rate in considered RoF system. The in-depth experimental evaluation and comparison with other ML techniques are envisaged for future work.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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